Real-time energy resources scheduling considering intensive wind penetration

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Abstract

The use of distributed energy resources, based on natural intermittent power sources, like wind generation, in power systems imposes the development of new adequate operation management and control methodologies.

A short-term Energy Resource Management (ERM) methodology performed in two phases is proposed in this paper. The first one addresses the day-ahead ERM scheduling and the second one deals with the five-minute ahead ERM scheduling.

The ERM scheduling is a complex optimization problem due to the high quantity of variables and constraints. In this paper the main goal is to minimize the operation costs from the point of view of a virtual power player that manages the network and the existing resources. The optimization problem is solved by a deterministic mixed-integer non-linear programming approach.

A case study considering a distribution network with 33 bus, 66 distributed generation, 32 loads with demand response contracts and 7 storage units and 1000 electric vehicles has been implemented in a simulator developed in the field of the presented work, in order to validate the proposed short-term ERM methodology considering the dynamic power system behavior.

Keywords: Mixed-integer non-linear programming; Short-term energy resources management; Smart grid; Virtual power player;

1. Nomenclature

c_{EGE}	Excess generated energy cost
$c_{Cut(b)}$	Consumption curtailment cost for bus *b*
$c_{Red(b)}$	Consumption reduction cost for bus *b*
$c_{Supplier}$	Supplier energy cost
$c_{StorageCharge}$	Storage charge cost
$c_{StorageDischarge}$	Storage discharge cost
$c_{V2GCharge}$	V2G charge cost
$c_{V2GDischarge}$	V2G discharge cost
c_{NSP}	Non-supplied power cost
$c_{DG(g)}$	Generation cost of generation unit *g*
ng	Total number of generators
nb	Total number of buses
P_{Load}	Load power
$P_{Cut(b)}$	Consumption curtailment for bus *b*
$P_{CutMax(b)}$	Maximum consumption curtailment in bus *b*
$P_{DG(g)}$	Generation power of generation unit *g*
$P_{DGMax(g)}$	Maximum generation power of generation unit *g*
$P_{DGMin(g)}$	Minimum generation power of generation unit *g*
P_{EGE}	Excess generated energy cost
$P_{Red(b)}$	Consumption reduction for bus *b*
$P_{RedMax(b)}$	Maximum consumption reduction in bus *b*
$P_{Supplier}$	Supplier power
$P_{Storage}$	Storage power
$P_{StorageInitial}$	Initial stored power
$P_{StorageCharge}$	Storage charge power
$P_{StorageChargeMax}$	Maximum storage charge power
$P_{StorageDischarge}$	Storage discharge power
$P_{StorageDischargeMax}$	Maximum storage discharge power
$P_{StorageMax}$	Maximum storage power
P_{V2G}	V2G power
$P_{V2GInitial}$	Initial stored power in V2G batteries
$P_{V2GCharge}$	Storage charge power in V2G batteries
$P_{V2GChargeMax}$	Maximum storage charge power in V2G batteries

$P_{V2GDischarge}$	Storage discharge power in V2G batteries
$P_{V2GDischargeMax}$	Maximum storage discharge power in V2G batteries
P_{V2GMax}	Maximum storage power in V2G batteries
P_{NSP}	Non-supplied power
$X_{Cut(b)}$	Binary variable for consumption curtailment, for bus *b*
$X_{DG(g)}$	Binary variable for generation unit *g*
$X_{Storage}$	Binary variable for storage charge
$Y_{Storage}$	Binary variable for storage discharge
X_{V2G}	Binary variable for V2G charge
Y_{V2G}	Binary variable for V2G discharge

1. Introduction

The increasing use of Distributed Generation (DG), mainly based on renewable energy resources, and other Distributed Energy Resources (DER), including DG, Demand Response (DR) programs, storage systems and electric and plug-in hybrid vehicles poses new challenges to Power Systems planning and operation. Also the introduction of liberalized markets in the electricity sector has caused significant changes in power systems agents relationships. DER use in distribution network has been increased significantly [1, 2], bringing new challenges to power systems agents and leading to the smart grid concept [3-8].

In some cases, the investment made in RES is not used in its full extent. In some periods, with high wind generation and low demand consumption, a wind curtailment is also necessary. Presently, operation planning methods are not adequate to the characteristics of most of DER and even with a lot of ongoing research work some problems remain unsolved. This is the case of real-time DER management which should take into account all the relevant technical and economic issues [9, 10].

The high number of wind energy is worrisome, since wind power is stochastic, especially in the very short term (e.g., over any given hour, 30 minutes, 15 minutes or 5 minutes period) [11]. This has created a completely new challenge to the system operators so maintain continuously balance electricity supply and demand.

The main difficulties with renewable energy resources are the dispatchability and reliability problems associated with their operation. The output of some renewable generation, such as wind generators and photovoltaic systems, is determined by the climate and weather conditions and operating patterns will therefore follow these natural conditions. The intermittent nature of these sources leads to an output which often does not suit the load demand profile. Smart grids introduce new management concepts with new operation methods for adequately scheduling renewable based generation and all DER.

Storage systems and electric vehicles could be very useful in the Energy Resources Management (ERM) process. These units increase the consumption in generation surplus cases (charge batteries) and increase the generation in shortage generation cases (discharge batteries). Demand response programs can be used in a more flexible way guaranteeing that the most costly generation resources are managed so that operation costs are kept within acceptable limits [12, 13]. The new context includes a large number of players (electricity consumers, DG owners, aggregating entities such as Virtual Power Players (VPP) [14-16], and system operators) acting in competitive Electricity Markets.

Short-Term energy resource management is a very relevant task in modern energy systems [9, 10]. It consists in correctly scheduling the available DER in order to reduce the operation costs. The number of variables considered in this approaches, and the need for obtaining a rapid response, requires the usage of advanced optimization techniques, such as artificial intelligence techniques, namely metaheuristics such as Particle Swarm Optimization, Genetic Algorithms or Simulated Annealing [7, 9, 17-20].

The coordination of all these resources is a quite challenging issue requiring distributed intelligence according to the concept of the smart grid [3, 6, 8]. This can be achieved through an integration of the behavior and actions of all users connected to it, and so, adequately scheduling renewable based generation and all DER, including the available load curtailment opportunities [1, 10].

This work contributes to overcome this situation conceiving, developing and implementing methodologies adequate for energy resource management in a distribution network, considering intensive penetration of DG, storage, electric vehicles and load curtailment opportunities enabled by demand response programs in the context of future power systems. The proposed methodologies are based on the characteristics of the problem and of the involved resources.

2. Energy Resource Management Methodology

Proper use of optimization techniques in the DER real-time scheduling is very relevant for smart grids. This is mainly due to the lack of accuracy in wind forecasting when the forecasting anticipation is increased. In [21] the authors demonstrate that wind forecasting can be very accurate for very short-term forecasting, using the last 5 hours of wind speed data to predict the next 5 minutes. This methodology can be used in this case to update 5 minutes ahead optimization input data. In [22] very short-term wind forecasting is also discussed for a real world application using data provided by Hydro Tasmania. A 2.5 minutes horizon is proposed in the used neuro-fuzzy methodology with less than 4% error. However, the forecast accuracy significantly drops when the time horizon is extended, with much higher errors when the prediction is made several hours ahead, namely for medium-term forecasting, with over 6 hours of anticipation.

Due to the difficulties of having accurate forecasting for natural resources, mainly due to forecast wind, the scheduling of energy resources should be undertaken with little anticipation. This leads to the proposal of a two-phase short-term energy resources scheduling, with different time anticipations (1 hour and 5 min) (Figure 1), each one considering the most updated forecasts, the already established contracts and market transactions and the market opportunities. The authors propose a new methodology to the real-time energy resource management that considers all the referred resources and aims at minimizing the operation costs. The developed methodology considers two different algorithms. The first one is used in each hour and the objective function consists in minimizing the operation cost. The difference between the energy resource scheduling computed in the previous day and the energy resource scheduling necessary to respond to the forecasted load demand. The second one is run in real-time for each period of 5 minutes [23]. It considers the adjustment according to the forecast of generation to the verified load demand. The difference between algorithms concerns the resources managed by each one. All the resources (generators, storage units, electric vehicles, demand response programs, and the intra-day market) are considered by the first algorithm. The second algorithm (5 minutes) only manages the connected generators (spinning reserve) with available power capacity, storage units, electric vehicles, demand response with load reduction contracts, and considers market penalties. The main goal is minimize the operation cost and minimize the impact in the day ahead and hour ahead energy resources scheduling. Considering these goals the aggregator reduces the operation costs and at same time the market penalties.

To test the methodology, a distribution network has been implemented in an Power Systems Simulation Tool (PSST) [24]. In each period of optimization, PSST exports the instant data (bus voltages, generation, load consumptions, line power flows, etc) to optimization tool software (OTS). The inputs to the algorithms of optimization are the actual data of generation and consumption sent by PSST and existent data base with equipment characteristics, DR contracts, and day-ahead electricity market information.

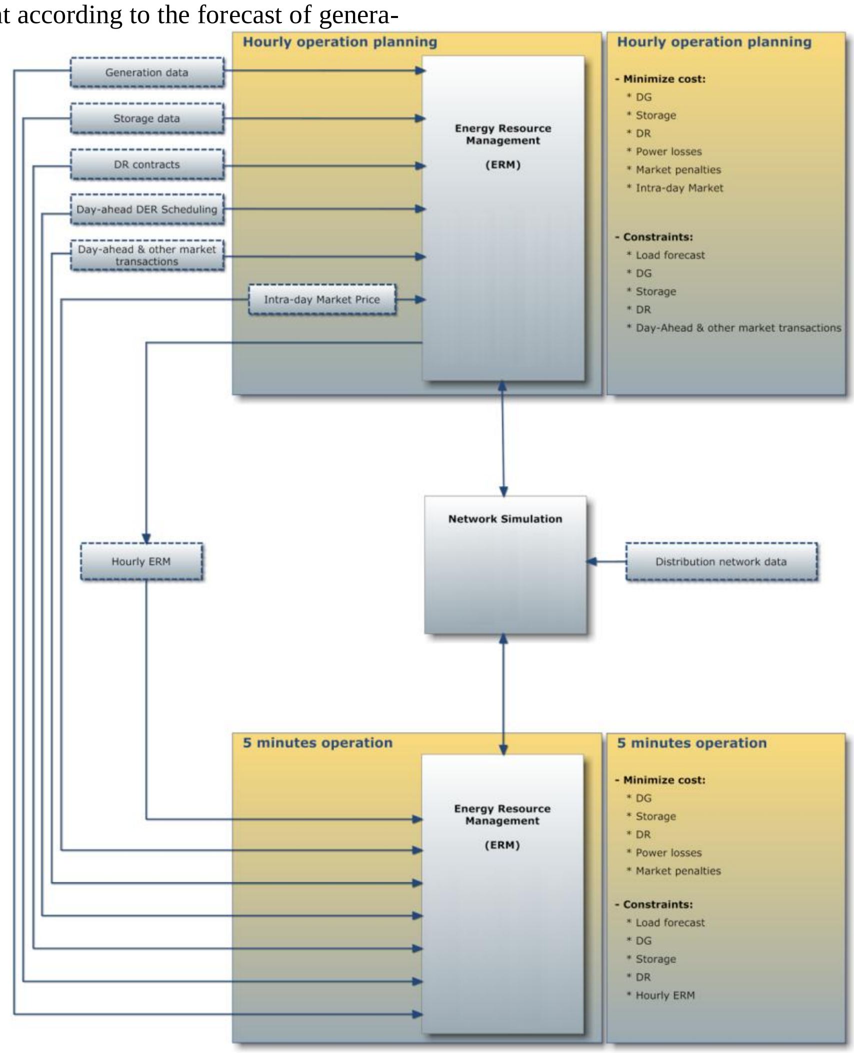

Fig. 1. Proposed methodology architecture

2.1. Mathematical formulation

This sub-section presents the mathematical formulation of the problem proposed to be solved. This problem is classified as mixed-integer non-linear. The objective function (1) of this mixed-integer non-linear model is formulated with the aim of finding the minimal cost of supplying the demand.

Minimize

$$f = \begin{pmatrix} P_{Supplier} \times c_{Supplier} + \sum_{g=1}^{ng} (P_{DG(g)} \times c_{DG(g)}) \\ - P_{StorageCharge} \times c_{StorageCharge} \\ + P_{StorageDischarge} \times c_{StorageDischarge} \\ - P_{V2GCharge} \times c_{V2GCharge} \\ + P_{V2GDischarge} \times c_{V2GDischarge} \\ + P_{NSP} \times c_{NSP} + P_{EGE} \times c_{EGE} \\ + \sum_{b=1}^{nb} \begin{pmatrix} P_{Cut(b)} \times c_{Cut(b)} \\ + P_{Red(b)} \times c_{Red(b)} \end{pmatrix} \end{pmatrix} \quad (1)$$

Two demand response capacities (consumption reduction and consumption curtailment) are considered as a resource. The existence of storage units and several generators, as well as the energy supplied by a supplier, are also considered.

Equations (2) to (13) refer to the constraints that are considered. Equation (2) refers to the first Kirchhoff Law or power balance constraint.

$$\begin{aligned} & P_{Supplier} + \sum_{g=1}^{ng} P_{DG(g)} + P_{StorageDischarge} + P_{V2GDischarge} \\ & + P_{NSP} + \sum_{b=1}^{nb} \left(P_{Cut(b)} + P_{Red(b)} \right) \\ & = P_{Load} + P_{StorageCharge} + P_{V2GCharge} + P_{EGE} \end{aligned} \quad (2)$$

Equations (3) to (7) represent the constraints concerning the maximum capacity considering the available resources, for both generation (3, 4) and load response (5, 6), and for storage units (7). In the consumption curtailment program, the participation of each load only can be by its total curtailment power.

$$P_{DG(g)} \le P_{DGMax(g)} \quad (3)$$

$$P_{DG(g)} \ge P_{DGMin(g)} \times X_{DG(g)};\ X_{DG(g)} \in \{0,1\} \quad (4)$$

$$P_{Cut(b)} = P_{Cut(b)} \times X_{Cut(b)};\ X_{CutA(b)} \in \{0,1\} \quad (5)$$

$$P_{Red(b)} = P_{RedMax(b)} \quad (6)$$

$$P_{Storage} \le P_{StorageMax} \quad (7)$$

Storage resources require a special treatment due to specific operation constraints. The discharge capacity is considered in equation (8) and the charge capacity in equation (9). In each instant, the battery only can be charging or discharging, as imposed in equation (10).

$$P_{StorageDischarge} \le P_{StorageDischargeMax} \times X_{Storage};\ X_{Storage} \in \{0,1\} \quad (8)$$

$$P_{StorageCharge} \le P_{StorageChargeMax} \times Y_{Storage};\ Y_{Storage} \in \{0,1\} \quad (9)$$

$$X_{Storage} + Y_{Storage} \le 1;\ X_{Storage} \text{ and } Y_{Storage} \in \{0,1\} \quad (10)$$

It is also necessary to impose that it is not possible to discharge more than the stored energy (11). Similarly, the power to be charged plus the power stored cannot be higher than the total storage resource capacity (12). Finally, the storage state is obtained considering the initial stored energy, the charge, and the discharge in each time period (13).

$$P_{StorageDischarge} - P_{StorageInitial} \le 0 \quad (11)$$

$$P_{StorageCharge} + P_{StorageInitial} \le P_{StorageMax} \quad (12)$$

$$P_{Storage} = P_{StorageInitial} - P_{StorageDischarge} + P_{StorageCharge} \quad (13)$$

Electric vehicles with gridable capability (V2G) resources require a special treatment due to specific operation constraints. The discharge capacity is considered in equation (14) and the charge capacity in equation (15). In each instant, the battery only can be charging or discharging, as imposed in equation (16).

$$P_{V2GDischarge} \le P_{V2GDischargeMax} \times X_{V2G};\ X_{V2G} \in \{0,1\} \quad (14)$$

$$P_{V2GCharge} \le P_{V2GChargeMax} \times Y_{V2G};\ Y_{V2G} \in \{0,1\} \quad (15)$$

$$X_{V2G} + Y_{V2G} \le 1;\ X_{V2G} \text{ and } Y_{V2G} \in \{0,1\} \quad (16)$$

It is also necessary to impose that it is not possible to discharge more than the stored energy (17). Similarly, the power to be charged plus the power stored cannot be higher than the total storage resource capacity (18). Finally, the storage state is obtained considering the initial stored energy, the charge, and the discharge in each time period (19).

$$P_{V2GDischarge} - P_{V2GInitial} \le 0 \quad (17)$$

$$P_{V2GCharge} + P_{V2G} \le P_{V2GMax} \quad (18)$$

$$P_{V2G} = P_{V2GInitial} - P_{V2GDischarge} + P_{V2GCharge} \quad (19)$$

2.2. Short-term scheduling simulator

In this work the DICOPT solver is used to the MINLP approach for the short-term energy resources management, the OTS is used for interface between the results of scheduling and the simulation tool [28-30]. To simulate the use of DER in power systems, it is necessary to create models in simulation tools to test scheduling solutions prior to actual implementation. The tool for simulation of electricity network and energy resources used to apply the proposed methodology is PSST.

The choice of these three software packages fulfilled the requirements, providing us with powerful mathematical resources of DICOPT solver, and the use of the OTS with the advantage of an efficient connection with the PSST power system simulator. This tool allows build custom models using PSST Design Editor. PSST has been widely used in the study of distributed energy resources [31-37].

To simulate the distribution network for the hourly operation planning, the authors had to implement the network in PSST and to create models of distributed generation units, loads, lines and substation. During the simulation, PSST receives information concerning distribution network data, network state, DG and DR short-term scheduling resulting from the optimization process. The optimization process, needs the following data: generation data, generation costs, DR contracts, day-ahead DER scheduling and the intra-day market price, with the objective to minimize the cost of the DG, load curtailment and the intra-day market.

PSST has the capability of interfacing with OTS commands and toolboxes through a special interface. OTS programs or block-sets that are to be interfaced with PSST must be designed and saved as an OTS program file. Then, a user-defined block must be provided in PSST, with the necessary inputs and outputs, to interface the OTS file. In this paper, an interfacing block has been created in PSST to link the OTS files defined within the block.

Fig. 2 shows components and the connection between the PSST and OTS.

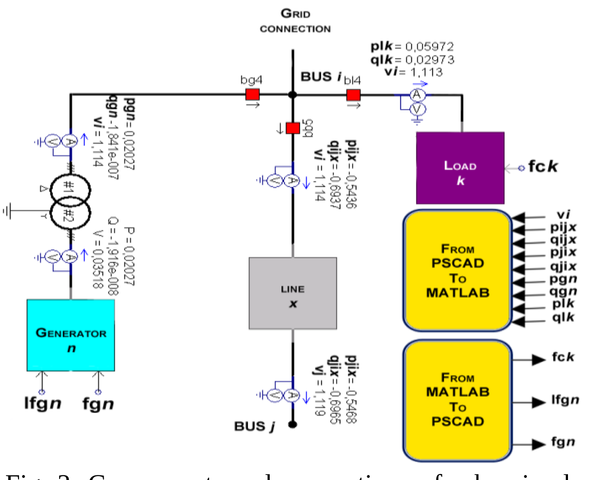

Fig. 2. Components and connections of a bus implemented in PSST

where:

pg*n*	Active power of DG unit *n* in BUS *i*
qg*n*	Reactive power of DG unit *n* in BUS *i*
v*i*	Voltage magnitude in BUS *i*
v*j*	Voltage magnitude in BUS *j*
pl*k*	Active power demand of load *k* in BUS *i*
ql*k*	Reactive power demand of load *k* in BUS *i*
pij*x*	Active power in line x from BUS *i* to BUS *j*
qij*x*	Reactive power in line x from BUS *i* to BUS *j*
pji*x*	Active power in line x from BUS *j* to BUS *i*
qji*x*	Reactive power in line x from BUS *j* to BUS *i*
fc*k*	Load control variable of load *k*
Ifg*n*	Max. instantaneous active power generator of DG unit *n*
fg*n*	Generator control variable of DG unit *n*

The network values obtained for period *t* and with load forecast and generation forecast for period *t*+1, are important data for optimization process. The obtained optimized solution is sent to PSST, through the following variables: the load control variable in each load, the maximum instantaneous active power in each distributed generation unit, and the generator control variable in each distributed generation unit. These variables will set the new state of the generators and loads.

4. Case study

The case study shows the simulation of a distribution network with high DER penetration using PSST simulation tool and DICOPT solver to optimize the energy resources usage, and OTS to interface between the optimization and the simulation tool. The method considers the 5 minutes operation planning, in each phase, all the available resources (DG, demand response, electric vehicles and storage) respecting their technical limits, contracts, day-ahead and intra-day scheduling, and aims at minimizing the VPP operation costs.

The simulator will iterate with the optimization of the DER short-term scheduling, in terms of the 5 minutes operation planning during 2 hours scenario. The case study was implemented on the distribution network with 33 buses, from [19, 25], with load and Distributed Generation (DG) evolution prediction for the year 2040 [26], with 32 load, 66 DG and 1000 electric vehicles, 7 storage and 10 external supplier [26]. The electric vehicles use scenarios were developed in EVeSSi Simulator tool. This application allows the creation of different scenarios considering the trip parameters, electric vehicles classes and types parameters, and electric vehicles specific model parameters [27].

Short-term scheduling is used to reschedule the previously obtained schedule taking advantage of the better accuracy of short-term forecasting in order to obtain more efficient resource scheduling solutions.

The used optimization is based on a MINLP approach that has proved to achieve a satisfactory cost operating point in a competitive time.

The proposed methodology demonstrated to be able to provide users with significant cost reductions, lowering the power losses and resource use costs. Moreover, it includes a dynamic analysis of the power system simulation, which is based on the use of PSST.

Table 1 summarizes the considered energy resources costs for the case study and the number of DG units.

Table 1. Case study energy resource data.

Energy Resources		**Number of units**	**Price (m.u./MWh) case study**
Biomass		4	0.0500 – 0.0720
Cogeneration		15	0.0416 – 0.0600
Fuel cell		7	0.5833 – 0.8400
Hydro small		2	0.0458 – 0.0660
Photovoltaic		31	0.0167 – 0.0240
Waste to energy		1	0.0375 – 0.0540
Wind		6	0.0250 – 0.0360
Load	DR	32	1.000 – 15.000
Energy supply		10	0.5833 – 0.8400
Electric vehicles	Discharge	1000	0.2000 – 0.2500

The results of loads consumption and the DG (PV and Wind) prediction can be seen in Fig. 3.

The MINLP based optimization approach described in section 2 has been used for determining the Distributed Generation and Demand Response short-term scheduling for this case study. It is important to note that all 288 optimizations, each one undertaken for 5 minutes, are dependent from each other, because of the state of storage and state of electric vehicles. DER scheduling for period *t* is undertaken in period *t*-1, considering the operation state resulting from the schedule already used for the previous periods.

The methodology used to simulate the power system of this case study has been tested on a PC compatible with one Intel Xeon W5450 3.00 GHz processor, with 8 Cores, 12GB of random-access-memory (RAM) and Windows Sever Enterprise.

4.2. Results

Several results can be obtained from the simulations in this case study. The most important ones are energy scheduling in the day-ahead and in the hour-ahead and the transients effects between the scheduling periods. In this paper are presented the transient effects simulated in PSST.

Figure 4 shows the results in PSST of an example of the several energy resources evolution along a set of periods in bus 18. In Figure 5 is possible to see an example of the energy in a storage unit and an electric vehicle for the same periods of time

5. Conclusions

This paper presented a short-term energy resource management methodology involving day-ahead and five-minutes ahead scheduling. Short-term scheduling is used to reschedule the previously obtained schedule taking advantage of the better accuracy of short-term wind and solar generation and demand consumption forecasting in order to obtain more efficient resource scheduling solutions.

The proposed method considers distributed generators, storage units, electric vehicles and two distinct demand response programs –consumption reduction and consumption curtailment.

The optimization process use a deterministic approach mixed integer non-linear programming (MINLP). The obtained feasibility solution is technically validated using realistic power system simulation, based on PSST.

The presented case study is based on a 33 bus distribution network with distributed generation, storage units, electric vehicles and controllable loads.

Acknowledgements

This work is supported by FEDER Funds through COMPETE program and by National Funds through FCT under the projects FCOMP-01-0124-FEDER: PEST-OE/EEI/UI0760/2011, PTDC/EEA-EEL/099832/2008, and PTDC/SEN-ENR/099844/2008.

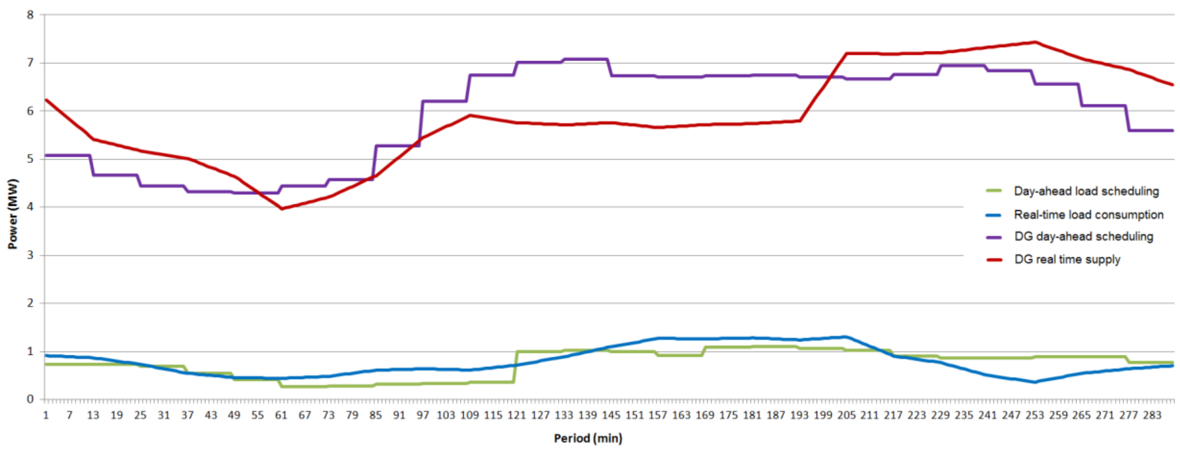

Fig. 3. Load forecasting and the DG forecasting.

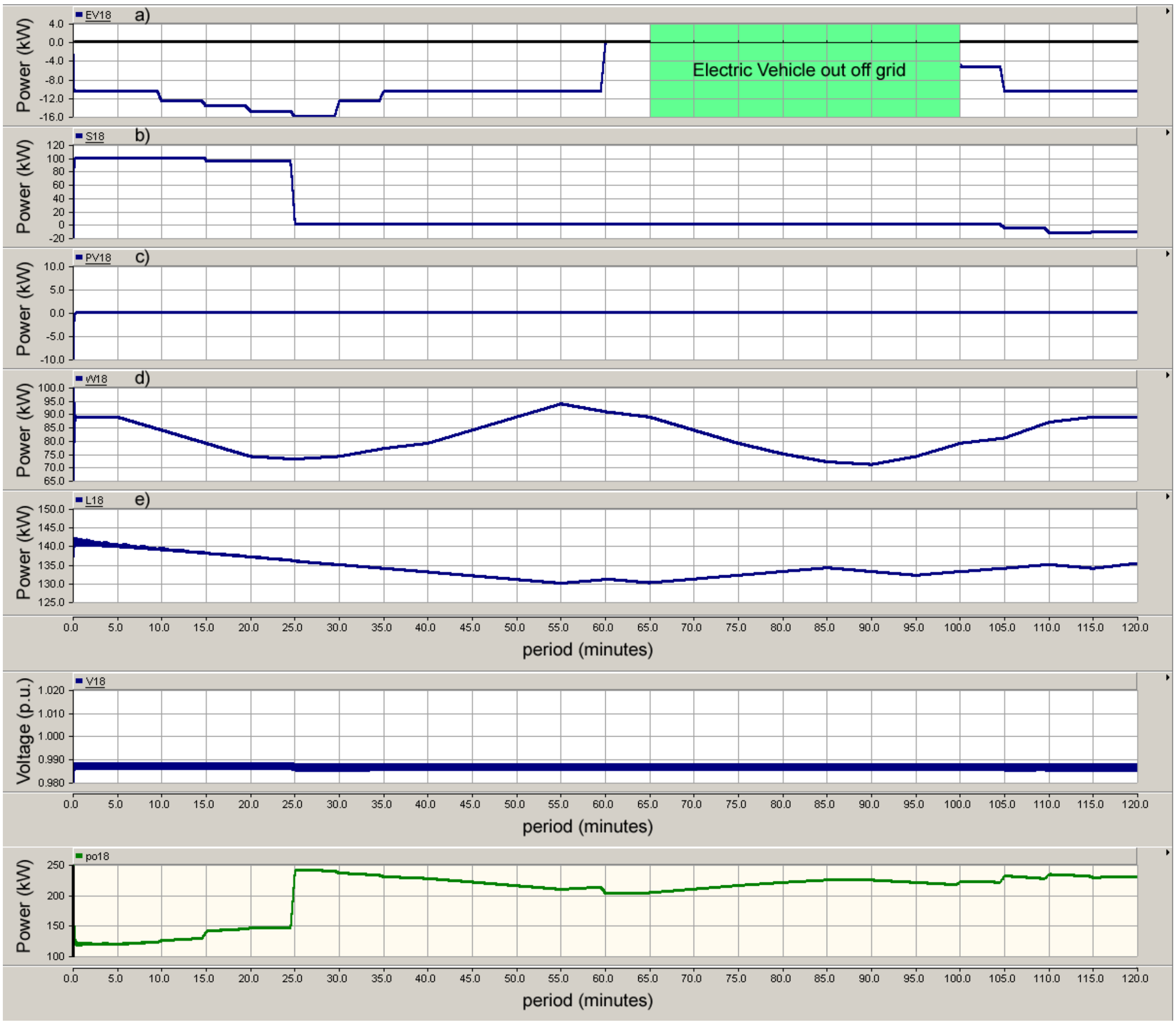

Fig. 4. Example of evolution of energy resources (EV – Electric Vehicle, S – Storage, PV – Photovoltaic, W – Wind, L – Load) and voltage (V)

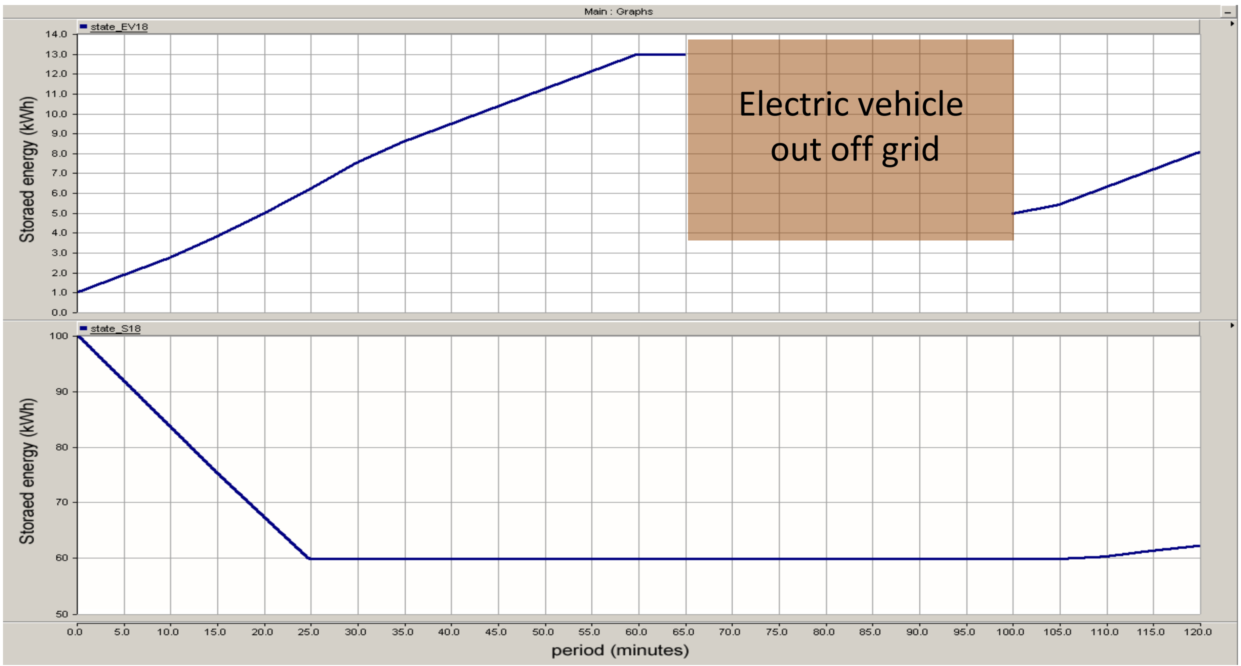

Fig. 5. Example evolution of energy in a storage unit and in a electric vehicle batteries

References

[1] H. Morais, P. Kadar, P. Faria, Z. A. Vale, and H. M. Khodr, "Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming," *Renewable Energy,* vol. 35, pp. 151-156, Jan 2010.

[2] H. M. Khodr, M. R. Silva, Z. Vale, and C. Ramos, "A probabilistic methodology for distributed generation location in isolated electrical service area," *Electric Power Systems Research,* vol. 80, pp. 390-399, Apr 2010.

[3] IEEE. (2011, *IEEE SMART GRID*. Available: http://smartgrid.ieee.org/

[4] Kim Jinho and Park Hong-Il, "Policy Directions for the Smart Grid in Korea," *Power and Energy Magazine, IEEE,* vol. 9, pp. 40-49, 2011.

[5] I. K. Song, K. D. Kim, J. Kelly, and C. Thomas, "Local Green Teams," *Ieee Power & Energy Magazine,* vol. 9, pp. 66-74, Jan-Feb 2011.

[6] Li Fangxing, Qiao Wei, Sun Hongbin, Wan Hui, Wang Jianhui, Xia Yan, Xu Zhao, and Zhang Pei, "Smart Transmission Grid: Vision and Framework," *Smart Grid, IEEE Transactions on,* vol. 1, pp. 168-177, 2010.

[7] Z. A. Vale, P. Faria, H. Morais, H. M. Khodr, M. Silva, and P. Kadar, "Scheduling Distributed Energy Resources in an isolated grid - An Artificial Neural Network Approach," *Ieee Power and Energy Society General Meeting 2010,* 2010.

[8] European Commission, "European SmartGrids Technology Platform - Vision and Strategy for Europe's Electricity Networks of the Future," E. Communities, Ed., ed, 2006.

[9] M. Silva, H. Morais, and Z. A. Vale, "Distribution network short term scheduling in Smart Grid context," in *Power and Energy Society General Meeting, 2011 IEEE*, 2011, pp. 1-8.

[10] A. Borghetti, M. Bosetti, S. Grillo, S. Massucco, C. A. Nucci, M. Paolone, and F. Silvestro, "Short-Term Scheduling and Control of Active Distribution Systems With High Penetration of Renewable Resources," *Ieee Systems Journal,* vol. 4, pp. 313-322, Sep 2010.

[11] CEPOS, "Wind Energy - The case of Denmark," Center for Politiske Studier, Copenhagen, DenmarkSeptember 2009.

[12] ISO/RTO Council, "North American Wholesale Electricity Demand Response Program Comparison," 2011.

[13] M. H. Albadi and E. F. El-Saadany, "A summary of demand response in electricity markets," *Electric Power Systems Research,* vol. 78, pp. 1989-1996, Nov 2008.

[14] C. Kieny, B. Berseneff, N. Hadjsaid, Y. Besanger, and J. Maire, "On the concept and the interest of Virtual Power plant: some results from the European project FENIX," *2009 Ieee Power & Energy Society General Meeting, Vols 1-8,* pp. 1877-1882, 2009.

[15] K. E. Bakari and W. L. Kling, "Virtual power plants: An answer to increasing distributed generation," in *Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES*, 2010, pp. 1-6.

[16] D. Pudjianto, C. Ramsay, and G. Strbac, "Virtual power plant and system integration of distributed energy resources," *Iet Renewable Power Generation,* vol. 1, pp. 10-16, Mar 2007.

[17] M. R. Silva, Z. Vale, H. M. Khodr, C. Ramos, and J. M. Yusta, "Optimal Dispatch with Reactive Power Compensation by Genetic Algorithm," *2010 Ieee Pes Transmission and Distribution Conference and Exposition: Smart Solutions for a Changing World,* 2010.

[18] Jizhong Zhu, *Optimization of power system operation*. Piscataway, N.J.: Wiley-IEEE ; Chichester : John Wiley [distributor], 2009.

[19] P. Faria, Z. Vale, J. Soares, and J. Ferreira, "Demand Response Management in Power Systems Using a Particle Swarm Optimization Approach," *Intelligent Systems, IEEE,* vol. PP, pp. 1-1, 2011.

[20] T. Sousa, H. Morais, Z. Vale, P. Faria, and J. Soares, "Intelligent energy resource management considering vehicle-to-grid: A simulated annealing approach," *Accepted for Publication on IEEE Transaction on Smart Grid, Special Issue on Transportation Electrification and Vehicle-to-Grid Applications,* 2011.

[21] Sérgio Ramos, João Soares, Zita Vale, and Hugo Morais, "A Data Mining Based Methodology for Wind Forecasting," presented at the 16th International Conference on Intelligent System Applications to Power Systems (ISAP 2011), Crete, Greece, 2011.

[22] C. W. Potter and M. Negnevitsky, "Very short-term wind forecasting for Tasmanian power generation," *Ieee Transactions on Power Systems,* vol. 21, pp. 965-972, May 2006.

[23] California ISO, "Renewables Integration Market Vision & Roadmap Day-of Market," Initial Straw Proposal07/06/2011 2011.

[24] PSCAD, "Applications of PSCAD / EMTDC," 2008.

[25] M. E. Baran and F. F. Wu, "Network Reconfiguration in Distribution-Systems for Loss Reduction and Load Balancing," *Ieee Transactions on Power Delivery,* vol. 4, pp. 1401-1407, Apr 1989.

[26] P. Faria, Z. A. Vale, and J. Ferreira, "Demsi — A demand response simulator in the context of intensive use of distributed generation," in *Systems Man and Cybernetics (SMC), 2010 IEEE International Conference on*, 2010, pp. 2025-2032.

[27] J. Soares, "Modified PSO for day-ahead distributed energy resources scheduling including vehicle-to-grid," Master degree thesis, Polytechnic of Porto, Portugal, 2011.

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